

# Solutions of economic load dispatch problems for hybrid power plants using Dandelion optimizer

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## ABSTRACT

In this paper, an economic load dispatch problem (ELD) is solved for reaching optimal power output of hybrid systems in addition to cost minimization. The systems consider the forbidden working zones (FWZs), dynamic load demand, wind farms, and solar photovoltaic fields (SPs). The cost minimization solutions for the ELD problem are found by applying the Dandelion optimizer (DO), the salp swarm algorithm (SSA), and the particle swarm optimization (PSO). In the study case, the power system consists of six thermal power plants (TPs), two wind farms, and two SPs. In addition, the variation of load demand over 24 hours of one day is applied. DO and SSA can achieve the best cost of \$15443.0753 for the first system, but PSO cannot. However, DO is the most stable method reaching the standard deviation of 0.0184 for fifty runs but that of SSA and PSO is about 1.0439 and 8.9664. For the second system, DO can reach smaller cost than PSO by \$11.17, \$137.74 and \$323.09 for the best, mean and worst solutions among fifty found solutions. As a result, DO is strongly recommended for solving the ELD problem.

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## 1. INTRODUCTION

One of the most critical problems in power system optimization operation is economic load dispatch (ELD) due to the considerable cost reduction based on found optimal generation solutions. These optimal solutions for ELD bring huge benefits by reducing operation costs and decreasing the adverse effects on nature [1]. The previous studies of ELD concentrated on solving the problem with a constant load demand value. Besides, thermal power plants (TPs) were the major power source, accounting for a higher rate than others. Lately, the conventional ELD has been expanded, considering new features in terms of load demand characteristics, highly complicated constraints, solar and wind energy [2]. These newly added features on the former ELD are generally named "expanded economic load dispatch" (EELD). Almost all previous studies about the ELD problem have aimed at reducing the entire fuel expenditure (EFE) as the main objective function. However, in the EELD problem, various objective functions are examined, such as minimizing the EFE, and minimizing the total emissions (TE). The presence of renewable energy sources (RESs) such as wind and solar energies is also evaluated alongside their uncertainty characteristics. Using these RESs is acknowledged as the best option for reducing the EFE of TPs. In particular, wind farms and solar photovoltaic

fields (SPs) can depressurize TPs during peak load demand [3], [4]. This trend has drawn the attention of many researchers recently. Following the trend, this paper also focuses on solving EELD to achieve the goal of minimizing EFE as much as possible. Besides, the supplied power from both wind farms and SPs is evaluated.

Solving the EELD problem is not easy for researchers because the scale, the number of control variables, and the number of complicated constraints is significantly greater than in ELD. Hence, meta-heuristic methods are acknowledged to be the most affordable computing methods for dealing with these problems. The implementation of meta-heuristic methods in ELD can easily be found in published studies such as improved firefly algorithm (IFA) [5], squirrel search optimizer (SSO) [6], hybrid swarm intelligence-based HSA (HIS-HAS) [7], harmonic search algorithm (HSA) [8], coyote optimization algorithm (COA) [9], marine predator algorithm (MPA) [10], [11], dynamically controlled particle swarm optimization (DCPSO) [12], modified social spider optimization (MSSO) [13], equilibrium optimizer algorithm (EOA) [14], tunicate swarm optimizer (TSO) [15], modified equilibrium algorithms (MEA) [16], evolutionary algorithm (EA) [17], K-mean cluster and elbow technique (KMC-ET) [18], the selection of hyper-heuristic [19], ameliorated dragonfly algorithm (ADA) [20], quantum-behaved particle swarm optimization (QPSO) [21], and distributed roust optimization (DRO) [22]. In general, the previous studies tried to apply new algorithms or improved existing ones to find more effective solutions. Metaheuristic algorithms are strong enough to successfully solve the ELD problem, but the quality of the solutions found is different due to the application and ability of the algorithms [23]. In addition to the application of metaheuristic algorithms, general algebraic modeling system (GAMS) software was used, and it successfully solved the problem when considering ramp rate limits and start-up costs for thermal units [24]. However, the studies have the same scope limits of not considering renewable energy and multi periods for optimizing the operation schedule.

This paper applies a novel meta-heuristic algorithm called the dandelion optimizer (DO) [25] to find optimal solutions for EELD. Besides, the forbidden working zones (FWZs) of TPs are also taken into account. In addition, the power supplied by wind farms and SPs is examined. Furthermore, the variation in load demand over a 24-hour period is taken into account. All these considerations are aimed at reaching the goal of minimizing EFE as much as possible. The results from DO are compared to other implemented algorithms, the salp swarm algorithm (SSA) [26] and particle swarm optimization (PSO) [27]. In summary, the contributions of the study can be summarized as follows:

- Successfully implement a novel meta-heuristic algorithm developed in early 2022 and two earlier algorithms, SSA and PSO, to find the optimal solutions for EELD. FWZs and other constraints, such as power balance and generation limits, are satisfied by the handling methods with the aid of the three applied methods.
- Present and demonstrate the superiority of DO over the most iconic algorithms in particular illustrations. The new DO algorithm is more favourable than two others in terms of the best-found solutions and the number of high-quality solutions.
- Show the vast contributions of both wind farms and SPs while reaching the goal of minimizing the EFE. The use of renewable energy can reduce the power supplied by thermal units, decreasing energy from thermal units, and minimizing the EFE.

Besides the Introduction, the rest of the whole study is structured as follows: the problem description is presented in section 2, the applied method will be introduced in section 3, the results obtained by the applied method are shown and discussed in section 4, and finally, the conclusions will be unveiled in section 5.

## 2. PROBLEM DESCRIPTION.

### 2.1. The main objective functions

As mentioned earlier, this paper focuses on reaching the objective function of minimizing EFE as large as possible. The mathematical expression of the function is as (1):

$$\text{Minimizing } EFE = \sum_{k=1}^{N_{TP}} \delta_k + \gamma_k TP_k + \beta_k TP_k^2 \quad (1)$$

Where  $N_{TP}$  is the number of TPs;  $\delta_k$ ,  $\gamma_k$ , and  $\beta_k$  are coefficients of TP; and  $TP_k$  is the supplied power from the  $k^{th}$  TP.

### 2.2. The involved constraints

The balance constraint: this constraint concerns the corresponding power between the supplying and consuming sides as shown in (2):

$$\sum_{k=1}^{N_{TP}} TP_k + WP + SP - (PoDe + PoLo) = 0 \quad (2)$$

where  $WP$  and  $SP$  are the power supplied by wind farms and SPs; and  $PoDe$  and  $PoLo$  are power demand and power loss, respectively.

Constraints on power generation and FWZs: all TPs in the system must strictly impose the constraints in (3) and (4):

$$TP_{k,min} \leq TP_k \leq TP_{k,max} \quad (3)$$

$$TP_k \in \begin{cases} TP_{k,min} \leq TP_k \leq TP_{m1}^l \\ TP_{km-1}^u \leq TP_k \leq TP_{mk}^l; m = 2, \dots, q \\ TP_{kq}^u \leq TP_k \leq TP_{k,max} \end{cases} \quad (4)$$

Where  $TP_{k,min}$  and  $TP_{k,max}$  are the lower and upper limits of TP  $k$ ; and  $q$  is the number of FWZs belonging to TP  $k$ .

The constraint of power generation from SPs: the supplied power from SPs must be satisfied by in (5) and (6):

$$\sum_c^{Ns} SP \leq 0.8 \times PoDe \quad (5)$$

$$SP_c^{min} \leq |SP_c| \leq SP_c^{max} \quad (6)$$

Where  $\sum_c^{Ns} SP$  is total supplied power from solar power plant;  $SP_c$  is the supplied power of solar power plant  $c$ ;  $SP_c^{min}$  and  $SP_c^{max}$  are the minimum and maximum supplied power of solar power plant  $c$ .

### 3. METHOD

Dandelion optimizer (DO) is a novel meta-heuristic algorithm proposed by Zhao *et al.* [25] in 2022. The algorithm simulates the journey of Dandelion seeds while leaving the flower until they land in another area to reproduce. Similar to other metaheuristic algorithms, DO also has solution generation technique and selection technique in which DO uses the idea from the leaving phase, the flying phase, and the landing phase for developing the generation technique. These phases are expressed as follows [25]:

a. The leaving phase:

The update of new solution in this phase is described as (7):

$$D_i^{new} = \begin{cases} D_i + \rho \times \sigma_1 \times \sigma_2 \times DF \times (D_{sl} - D_i), & rand < 1.5 \\ D_i \times RF, & else \end{cases} \quad (7)$$

Where,  $D_i^{new}$  and  $D_i$  are the new and previous position of Dandelion  $i$  ( $i=1 \dots Np$ ) and  $Np$  is the population size,  $\rho$  is the adaptive factor,  $\sigma_1$  and  $\sigma_2$  are the lifting coefficients,  $DF$  is the distribution factor,  $D_{sl}$  is the random selected Dandelion in the population and  $RF$  is the regulating coefficient.

b. The flying phase:

In this phase, all solutions are updated using (8):

$$D_i^{new} = D_i - \rho \times BR \times (D_{aver} - \rho \times BR \times D_i) \quad (8)$$

In the (8),  $BR$  is the Brownian motion and  $D_{aver}$  is the average position of all Dandelions in the population.

c. The landing phase:

In the last phase, the update of new solutions is simulated by (9):

$$D_i^{new} = D_{best} + LV \times \rho \times (D_{best} - D_i \times \omega) \quad (9)$$

Where  $D_{best}$  is the best position of all Dandelions at current iteration,  $LV$  is the value given by Levy distribution and  $\omega$  is the linear coefficient between 0 and 2.

### 4. RESULTS AND DISCUSSION

In this section, we applied three different meta-heuristic methods, including the DO [25], the SSA [26], and the PSO [27], to solve both the ELD and EELD problems. In particular, subsection 4.1 will present the results of solving the ELD with constant load demand to determine the best and worst applied methods. Next, in subsection 4.2, the two applied methods will be reapplied to solve the EELD with the consideration

of dynamic load demand and RESs. Besides, the power supplied from wind farms and SPs is evaluated. All of the related work is performed on a personal computer with a 2.2 GHz central processing unit and 8 GB of random memory access. MATLAB software version R2018a, on the other hand, is used to run all code and simulations.

#### 4.1. The results of ELD problem

In this section, the power system consists of six TPs, and its data are taken from [8]. The system must feed the load demand of 1263 MW adequately. PSO, SSA, and DO are used to determine the optimal power output of six TPs so that EFE is minimized. The initial control parameters such as population number, maximum iteration, and independent run number are 30, 50, and 50, respectively.

Figure 1 presents the results of the three applied methods after 50 independent runs. The blue line stands for the EFEs of PSO while the black and red ones represent the EFEs of SSA and DO. In the figure, DO shows the best performance by reaching more optimal EFE values than both SSA and PSO. On the contrary, PSO shows the poorest efficiency among the three applied methods since it cannot reach any optimal EFE value throughout 50 independent runs. Besides, the high performance of DO can be viewed in Figure 2. In this figure, the best convergences of the three applied methods among 50 independent runs are presented. DO only needs over 25 iterations to reach the optimal EFE value, while PSO cannot reach the same value.

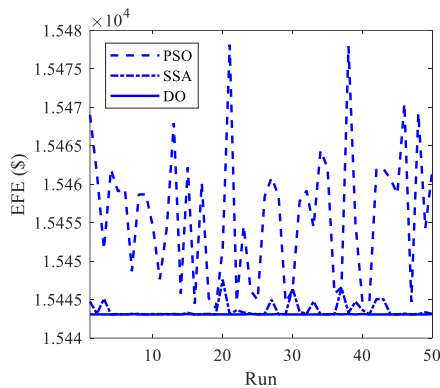


Figure 1. The results obtained by the three applied methods with 50 independent runs

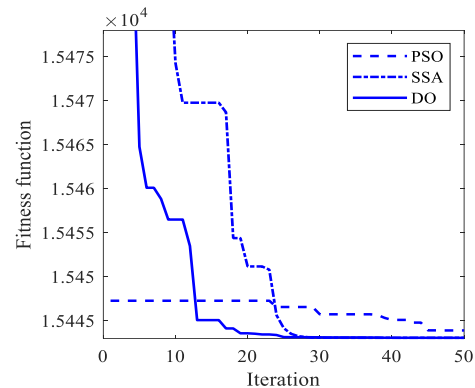


Figure 2. The best convergence curves of the three applied methods

Figure 3 depicts a comparison of various criteria, including the minimum EFE (Min EFE), average EFE (aver EFE), maximum EFE (max EFE), standard deviation (std), and time of execution (time). In the figure, DO completely outperforms PSO in all criterion comparisons. The min EFE and std are two important elements for evaluating the efficiency of a meta-heuristic algorithm. The min EFE and std of DO are 15443.0753 (\$) and 0.0184, respectively, while those of PSO are \$15443.9129 and 8.9664. About SSA, even though the method can find the same min EFE, but std value is still higher than DO. Moreover, other results on the remaining criteria given by SSA are also higher than DO. The savings on EFE value posted by DO over PSO on the first three criteria are \$0.8376, \$12.9236, and \$35.0204. As mentioned earlier, SSA can find the same min EFE as DO, but there are noticeable differences in aver EFE and max EFE. On these criteria, the savings on EFE of DO over SSA are 0.5511 for aver EFE and 4.4638 for max EFE. Furthermore, the observation on the time of execution of the three applied methods also indicates that DO is the fastest method. It takes DO 0.9844 second, SSA 1.3428 seconds, and PSO 1.1563 seconds. Clearly, DO is a simple structure and effective method among the three applied ones.

The results obtained by DO are also compared to other methods from previous studies, as shown in Table 1. In the table, the results given by DO are compared with IFA [5] and HHS [8]. The observation on these criteria indicates that DO not only reach the same min EFE as other methods but also obtains the highest stability with the smallest parameter setting. In fact, the mean and max EFE of DO are smaller than others, but it does not use higher parameter settings. DO only requires 30 and 50 for population and iteration number to while IFA used 45 for population and 30 for iteration number. HHS was not reported for the settings. Moreover, the aver EFE reached by DO is only 15443.1255 (\$/h), whereas the similar values reported by HHS and IFA are, respectively, 15450 (\$/h) and 15443.12 (\$/h). The max EFE of DO is 15443.1255 (\$/h), which is less than that of HHS at 15453 (\$/h) and IFA at 15443.52 (\$/h). On top of that, the value of std reached by DO is the best on the list, at only 0.0184, while that of HHS and IFA was not reported for comparison.

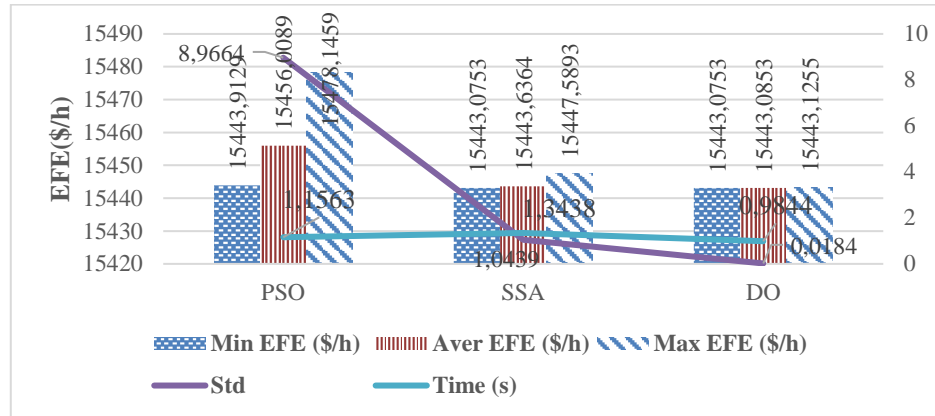


Figure 3. The results obtained by PSO, SSA and DO on different criteria

Table 1. The comparison of DO and other methods

Method	Min EFE (\$/h)	Aver EFE (\$/h)	Max EFE (\$/h)	Std	Population	Iteration number
IFA [5]	15443.075	15443.12	15443.52	-	45	30
HHS [8]	15449	15450	15453	-	-	-
PSO	15443.9129	15456.0089	15478.1459	8.9664	30	50
SSA	15443.0753	15443.6364	15447.5893	1.3438	30	50
DO	15443.0753	15443.0853	15443.1255	0.0184	30	50

#### 4.2. The results of EELD problem

In this section, DO and PSO are reapplied to solve the EELD problem by using the same initial control parameters as section 4.1. The power system is expanded by the presence of two wind farms and two SPs. The supplied power of both wind farms and SPs is taken from [28], [29]. Besides, the dynamic load demand over 24 periods with one hour for each is also employed.

Figure 4 presents the comparison of the total EFE of two methods over 24 hours. The results reached by DO are clearly better than those of PSO for all criteria. Particularly, DO reaches smaller min EFE, aver EFE and max EFE over 24 hours than PSO by \$11.17, \$137.74 and \$323.08, respectively. Figures 5(a) and 5(b) present aver EFE and max EFE of the two applied methods at each hour. The differences in EFE values reached by DO over PSO are relatively large in Figure 5(a), and the differences are greater in Figure 5(b), excluding hours 12-14. Notably, DO always reaches lower EFE values than those of PSO at each hour. Figure 6 shows the power output of six TPs, wind farms and SPs. It can be seen that thermal power plant 1 (TP1) accounts for a significant part of the total power output, while thermal power plant 6 (TP6) generates the smallest power. Besides, the EFE values are not the same at each hour. At the high load demand hours, EFE values are significantly greater than those of other hours with low load demand. In addition, the power supplied by wind farms and SPs also has a high impact on the hourly EFE, especially for the high load demand hours.

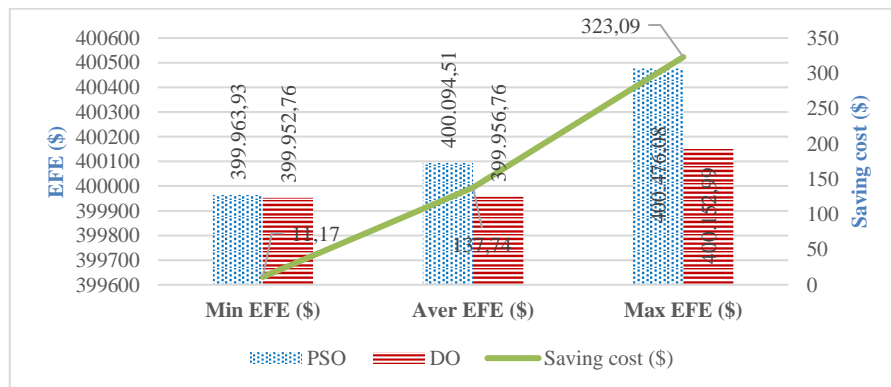


Figure 4. The cost values on different criteria reported by PSO and DO within 24

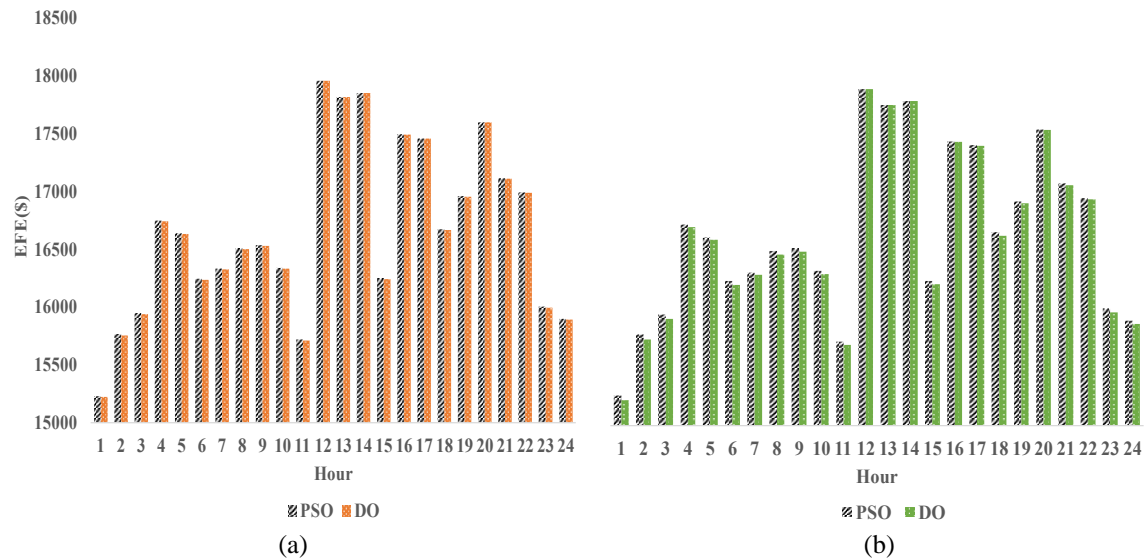


Figure 5. Hourly average and maximum cost value in one day obtained by DO and PSO (a) average cost values and (b) maximum cost values

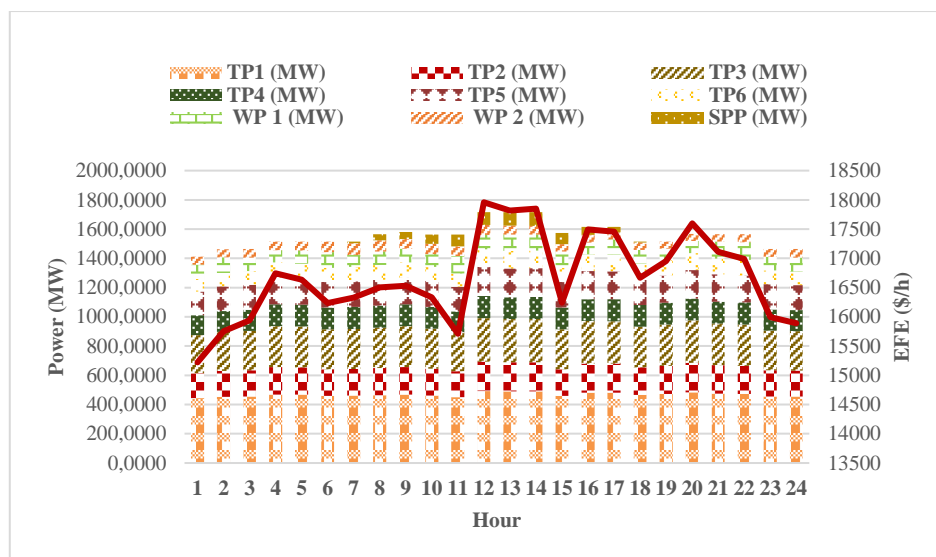


Figure 6. The optimal power outputs of all power plants found by DO

## 5. CONCLUSION

In this paper, DO was successfully implemented to solve both ELD and EELD problems. In the EELD, new features such as the dynamic load demand and the power supplied by both wind farms and SPs are evaluated. The results from solving the ELD problem indicate that DO is completely superior to both SSA and PSO in all comparisons. PSO shows the poorest performance among the three applied methods. Moreover, DO and PSO are reapplied to solve the EELD problem over 24 hours in one day. DO can find more optimal values of EFE than PSO during 50 independent runs, as both methods use the same population and maximum iteration. Therefore, DO is acknowledged as a highly effective search method, and it is strongly suggested for dealing with EELD problems. In the future, the performance of DO can be improved to a higher degree by applying several modifications to its update process for new solutions. On top of that, uncertainty of renewable energies such as wind speed and solar radiation will be considered and analyzed for showing the impact of energy instability on economic and technical issues of power systems. In addition, computation tool of GAMS software and complicated constraints such as spinning reserve, ramp rate limits and transmission line capacity will be considered in the upcoming research.

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